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The asymmetric Granger-causality analysis between energy consumption and income in the United States

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ABSTRACT

We investigated Granger-causality between variants of the energy consumption sources and Gross Domestic Product (GDP) for the United State of America (USA). To accomplish this objective we utilized a recent approach of asymmetric Granger-causality developed by Hatemi-J for the period January 1973–October 2011. Our results indicated presence of asymmetric Granger-causality between a few variants of energy consumption sources (i.e., Coal Consumption (CC), Natural Gas Consumption (NG), Primary Energy Consumption (PE), and Total Renewable Energy Consumption (TRE)) and GDP (all measured in growth rates). Additionally, when positive shocks are analyzed we found the evidence of unidirectional Granger-causality running from GDP growth rate to growth rate of CC and from growth rate of Total Electricity End Use (EC) to GDP growth rate. Additionally, we find significant evidence of bidirectional Granger-causality between NG and GDP, PE and GDP and TRE and GDP (all measured in growth rates). However, in case of negative shocks we find that the null hypothesis that growth rates in CC and TRE do not Granger-cause GDP growth rate is rejected at 5% level of significance. These results have important implications for research analysts as well as policy makers of the USA economy.

Contents

1. Introduction

Recently, the interest of researchers has shifted to analyzing the direction of Granger-causality between renewable energy sources and economic growth. This motivation comes, in particular, from three major reasons. First, it is expected that consumption of renewable energy sources (RES) will reduce the consumption of those sources of energy (particularly non-renewable i.e., NRES) that are highly contributing to the greenhouse gas emissions (GHGs), especially carbon dioxide (CO_2) emissions, which is considered as the main causes of global warming. Hence, as a consequence, environmental degradation can be minimized or to the extent possible can be reduced. Second, the substitution of non-renewable energy sources with renewable energy sources will occur without harming the economic growth rate of the economies. The third reason is the environmental awareness programs organized by different government or non-government agencies and profit and/or non-profit organizations at national and international levels. In total, the objectives of the studies were whether economic growth of the nation in question Granger-causes renewable energy consumption or vice-versa or there is evidence of bidirectional Granger-causality.

The conduit through which consumption of RES boosts the growth rate of the economy is a debatable topic among researchers and energy analysts. Nevertheless, the plausible mechanism has been explained in quite a few studies. For example, Domac et al. [1] and

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Chien and Hu [2] suggest that renewable energy might increase the macroeconomic efficiency and thereby boost the economic growth process.[1] Masui et al. [3] suggested some effective ways to address the issues related to the climate change; for example, adopting environmentally sustainable technologies, improving energy efficiency, forest conservation, reforestation, water conservation, or energy saving. Abulfotuh [4] suggested considering an immediate change in the composition of an energy resource portfolio due to the escalating demand for energy. Tiwari [5] suggested that the promotion of RES may also be helpful in mitigation of CO_2 emissions. As a consequence, it will reduce the negative impact of global warming on the economic growth. Hence, we expect that RES have great potential to solve a major part of global energy sustainability. In this regard Krewitt et al. [6] suggest that RES could provide as much as half of the world's energy needs by 2050.

Our observation from the exhaustive survey of Payne [7,8][2] and Ozturk [9] indicates that studies in this area have yielded mixed and often conflicting results for both developed and developing countries due to different methods, sample periods, and model specifications employed. Payne [10] found an absence of Granger-causality between renewable or non-renewable energy consumption and real GDP and thus provided support to the neutrality hypothesis for the U.S. during 1949–2006 with the application of the Toda–Yamamoto [11] approach. Bowden and Payne [12], for the U.S., for the period 1949–2006, by using the Toda–Yamamoto [11] approach, found bidirectional Granger-causality between commercial and residential primary energy consumption and real GDP, respectively. Further, their results indicated that industrial primary energy consumption Granger-causes real GDP. Bowden and Payne [13], for the U.S., by using the data from 1949 to 2006 and applying the Toda–Yamamoto [11] approach, showed the evidence of bidirectional Granger Granger-causality between commercial and residential non-renewable energy consumption and real GDP, respectively. Further, their results indicated significant evidence of unidirectional Granger-causality running from residential renewable energy consumption and industrial non-renewable energy consumption to real GDP. Payne [14] with the application of Toda–Yamamoto [11] approach for the period 1949–2007 found evidence of unidirectional Granger-causality running from biomass energy consumption to real GDP and hence provided support of the growth hypothesis. By the application of the Toda–Yamamoto [11] approach, for the period 1949–2006, Payne [15] found evidence for the absence of Granger-causality between coal consumption and real GDP, positive unidirectional Granger-causality running from real GDP to natural gas consumption, and positive unidirectional Granger-causality running from petroleum consumption to real GDP. Aslan and Çam [16] examine the Granger-causal relationship between nuclear energy consumption, economic growth, capital and labor for Israel, over the period of 1985–2009 using a bootstrap-corrected Granger-causality. They found that there exists unidirectional Granger-causality, which is running from nuclear energy consumption to GDP.

Pao and Tsai [17] examine the dynamic causal relationships between pollutant emissions, energy consumption and output of a panel of BRIC (i.e., Brazil, Russia, India and China) countries over the period 1971–2005, except for Russia (1990–2005). They found that in the long-run equilibrium energy consumption has a positive and statistically significant impact on emissions, while real output exhibits the inverted U-shape pattern associated with the Environmental Kuznets Curve (EKC) hypothesis with the threshold income of 5.393 (in logarithms). Further, in the short term, changes in emissions are driven mostly by the error correction term and short term energy consumption shocks, as opposed to short term output shocks for each country. The panel Granger-causality results indicate there is energy consumption–emissions bidirectional strong Granger-causality and energy consumption–output bidirectional long-run Granger-causality, along with unidirectional both strong and short-run causalities, from emissions and energy consumption, respectively, to output. Yildirim et al. [18] investigated the Granger-causal relationships among industrial production index, coal consumption and employment in the industrial sector for the period of 1973:1–2011:10 in the USA. After noticing that there are breaks in the regression model, the Hatemi-J test for cointegration was employed in the cases that take into account two possible regime shifts. They found that there is a long run relationship between industrial production and industrial coal consumption with the breaks at 1983:4 and 1998:4. Further, a negative relationship between coal consumption and industrial production for the period of 1973:1–1983:4 and positive relationship for 1983:5–1998:4 period was also found, however, for the last period that covers 1983:5–2011:10, the cointegration relationship turned to negative and the causal relationship between coal consumption and industrial production changes over time.

Yildirim et al. [19] using real GDP, employment, investment and kinds of renewable energy consumption in their empirical model for the USA found evidence of only one Granger-causal relationship which was running from biomass-waste-derived energy consumption to real GDP. No Granger-causal relationship was found between real GDP and all of the other renewable energy kinds such as total renewable energy consumption, geothermal energy consumption, hydroelectric energy consumption, biomass energy consumption and biomass-wood-derived energy consumption. That is using of energy from waste cause not only solving the dumping problems, but also it contributes to real GDP. Yildirim and Aslan [20] examine the relationship between energy consumption, economic growth, employment and gross fixed capital formation for 17 highly developed OECD countries by employing both the Toda–Yamamoto procedure which based on asymptotic critical values and the bootstrap-corrected Granger-causality test, since non-normality of the error term harms the validity of the Toda–Yamamoto procedure. They found that there exists unidirectional Granger-causality running from energy consumption to real GDP for Japan and bi-directional Granger-causality for Italy, New Zealand, Norway and Spain. Further, they found that there exists uni-directional Granger-causality from GDP to energy for Australia, Canada and Ireland whereas there is no Granger-causal nexus for all of other nine countries. Tugcu et al. [21] investigate the long-run and Granger-causal relationships between renewable and non-renewable energy consumption and economic growth by using classical and augmented production functions, and making a comparison between renewable and non-renewable energy sources in order to determine which type of energy consumption is more important for economic growth in the G7 countries for 1980–2009 period. Autoregressive Distributed Lag approach to cointegration was employed for this purpose. Also, they investigated Granger-causality among energy consumption and economic growth by employing a recently developed Granger-causality test by Hatemi-J [22]. They found that in the long-run either renewable or non-renewable energy consumption matters for economic growth and augmented production function is more effective in explaining the considered relationship. Further, they found the evidence of bidirectional Granger-causality for all countries in case of classical production function and mixed results for each country when the production function is augmented.

[1] This might be due to either the expansion of business and new employment opportunities brought by renewable energy industries that result in economic growth or through the import substitution of energy, which has direct and indirect effects on the increase of an economy's GDP and/or trade balance.

[2] For details, please refer to the original study by Payne [7,8] and Ozturk [9]. Besides Payne [7,8] and and Ozturk [9], Shahbaz et al. [36] and Tiwari [37,38] also have provided a comprehensive review of the literature and one may refer to those too.

Apergis and Payne [23] examine the relationship between renewable and non-renewable energy consumption and economic growth for 80 countries within a multivariate panel framework over the period 1990–2007. In their analysis the Pedroni's heterogeneous panel cointegration test shows a long-run equilibrium relationship between real GDP, renewable energy consumption, non-renewable energy consumption, real gross fixed capital formation, and the labor force with the respective coefficient estimates positive and statistically significant but with a little difference in the elasticity estimates with respect to renewable and non-renewable energy consumption. Further, they found from the panel error correction model that there is evidence of bidirectional Granger-causality between renewable and non-renewable energy consumption and economic growth in both the short- and long-run. Also, there is a bidirectional short-run Granger-causality between renewable and non-renewable energy consumption, indicative of substitutability between the two energy sources. Ocal and Aslan [24] investigated the relationship between renewable energy consumption, capital, labor, and economic growth in Turkey for the period of 1990–2010 using ARDL approach and Toda–Yamamoto Granger-causality tests. The empirical test results from the ARDL approach show that renewable energy consumption has a negative impact on economic growth, and ones from Toda–Yamamoto Granger-causality tests show that there is a unidirectional Granger-causality running from economic growth to renewable energy consumption. In the literature, most of the empirical results suggest feedback or growth hypothesis for developed countries, but this study suggests a conservation hypothesis for the relationship between renewable energy consumption and economic growth in Turkey. Renewable energy is an expensive energy source for developing countries, as abundant research studies have revealed that increase in income is a vital supporter behind increased renewable energy consumption. Although this does not mean that energy consumption is not vital for the Turkish economy, it could be stated that the role of renewable energy consumption is relatively smaller than the other sources. Also, this result has vital consequences regarding policy, as it suggests that renewable energy limitations do not seem to damage economic growth in Turkey. Pao and Fu [25] employ Brazil's yearly statistics from 1980 to 2010 to explore the Granger-causal relationships between the real GDP and four types of energy consumption: non-hydroelectric renewable energy consumption (NHREC), total renewable energy consumption (TREC), non-renewable energy consumption (NREC), and the total primary energy consumption (TEC). The cointegration test reveals a long-run equilibrium among Brazil's real GDP, labor, capital, and each of the four types of consumption. The development of the Brazilian economy has close ties with capital formation and labor force. The influence of NHREC/TREC on real output is positive and significant, while the impacts by NREC/TEC are insignificant. The results from the vector error-correction models reveal a unidirectional Granger-causality from NHREC to economic growth, a bidirectional Granger-causality between economic growth and TREC, and a unidirectional Granger-causality from economic growth to NREC or TEC without feedback in the long-run. These findings suggest that Brazil is an energy-independent economy and that economic growth is crucial in providing the necessary resources for sustainable development. Expanding renewable energy would not only enhance Brazil's economic growth and curb the deterioration of the environment, but also create an opportunity for a leadership role in the international system and improve Brazil's competition with more developed countries.

Kum et al. [26] examine the relationship between natural gas consumption, economic growth and capital by using G-7 countries data and a bootstrap-corrected Granger-causality test for the period 1970–2008. They found evidence of eight significant Granger-causal relationships. Specifically, for Italy, the Granger-causality is running from natural gas consumption to growth and for the United Kingdom vice-versa. For France, Germany and United States, there is evidence of bidirectional Granger-causality between natural gas and growth. Silva et al. [27] analyzed how an increasing share of Renewable Energy Sources on Electricity generation (RES-E) affects the Gross Domestic Product (GDP) and Carbon Dioxide (CO_2) emissions using a 3 variable Structural Vector Autoregressive (SVAR) methodology for the period 1960–2004. They through the impulse response functions (IRF) found that, for all countries in the sample, except for the USA, the increasing RES-E share had economic costs in terms of GDP per capita. There was also an evident decrease of CO_2 emissions per capita. The variance decomposition showed that a significant part of the forecast error variance of GDP per capita and a relatively smaller part of the forecast error variance of CO_2 per capita were explained by the share of RES-E.

It is worth noting that most previous studies are limited in scope to the applications of linear models (with exception to Tugcu et al. [21] and Hatemi-J and Uddin [28]). However, economic events and regime changes such as changes in the economic environment, changes in energy policy and fluctuations in energy price can cause structural changes in the pattern of energy consumption for a given time period of study. This creates room for an asymmetric Granger-causal relationship between energy consumption and economic growth. For example, in a state-wise analysis of the USA, Aslan [29] found that natural gas consumption in approximately over 60% of states follows a nonlinear behavior. Therefore, in the present study, we made an attempt to analyze the issue in a nonlinear framework by using a recently developed asymmetric Granger-causality approach of Hatemi-J [22]. This asymmetry in the Granger-causal relationship is captured by using the cumulative sums of positive and negative shocks. Further, following Hatemi-J [22], we also used a bootstrap simulation approach with leverage adjustment to generate critical values that are robust to non-normality and time-varying volatility.

With this background, in the present study, we analyzed the Granger-causal relation between a set of energy consumption measures and economic growth for the U.S. Variables considered in the study are Natural Gas Consumption (NG) (Billion Cubic Feet), Primary Energy Consumption (PE) Total (Trillion Btu), Coal Consumption (CC) (Thousand Short Tons), Total Electricity End Use (EC) (Billion Kilowatt hours), Total Renewable Energy Consumption (TRE) (Trillion Btu) and real GDP (real (2005) Dollars). Our study period is January 1973–October 2011 which is limited by the availability of the monthly data of the variables of our interest. For the analysis, we obtain data of primary energy consumption and electricity consumption from the U.S. Energy Information Administration (June 2012 Monthly Energy Review) and data of real GDP is obtained from http://www.bea.doc.gov/.[3]

We focus on the U.S. because of the important role that it plays in world energy markets. Soytas et al. [30] mention a few arguments in this regard. "First, according to the Statistical Abstract of the US (2006), GHG emissions in the US rose nearly 17% between 1990 and 2000 before leveling off in 2001 and 2002. Second, over that same time period, the US accounted for around

[3] It is important to mention that data of energy consumption sources are available with monthly observations while real GDP with annual observations. In order to match the observations GDP data is interpolated using a linear interpolation method. Here, we want to clarify that we have preferred to interpolate GDP instead of using industrial production data of which sufficient observations are available because first, interpolation of the data does not destroy the true property of the data (excepting some cases when an economy experiences abrupt changes so frequently); second, of course, industrial production is used in many studies as a proxy for GDP; however, it is not a true representative of the economies, particularly developed ones where major contributor in GDP is the service sector.

23–24% of the world's total CO_2 emissions from consumption of fossil fuels. Third, the US share of total world energy production has fallen slightly from 20% in 1990 to 18% and 17% in the years 2000 and 2003, respectively. Fourth, over the same time frame, the US share of total world energy consumption has remained fairly constant at around 24% (Soytas et al., [30], pp. 484).

Our contribution to the literature is three fold. First, to the best of our knowledge, this is the first study to employ such an approach in the area of energy economics for the USA for the variables considered. There are some studies that have used non-liner Granger-causality approach, but those have been unable to detect whether positive or negative shocks are promoting or hampering economic growth or vice-versa. Second, this is the first study to employ such an approach for variants of renewable energy consumption sources. Third, we found that asymmetry exists between CC and GDP, NG and GDP, PE and GDP, and TRE and GDP.

The rest of the paper is organized as follows. Section 2 discusses the methodology we employed. Section 3 presents empirical findings of the study and Section 4 gives conclusions and draws policy implications of the study.

2. Asymmetric causality tests

Hatemi-J [22][4] developed asymmetric Granger-causality tests taking ideas from Granger and Yoon [20] for integrated variables in a vector autoregressive (VAR) model Hatemi-J [22] argues that his test is asymmetric in the sense that it is developed with the idea that positive and negative shocks may have different Granger-causal impacts. Asymmetric Granger-causality tests developed by Hatemi-J [22] can be explained as follows. Let us assume that in a VAR we have two integrated variables, x_{1t} and x_{2t}, defined as the following random walk processes[5] of which we are interested in investigating the Granger-causal relationship:

$$x_{1t} = x_{1t-1} + e_{1t} = x_{10} + \sum_{i=1}^{t} e_{1i}, \tag{1}$$

and

$$x_{2t} = x_{2t-1} + e_{2t} = x_{20} + \sum_{i=1}^{t} e_{2i}, \tag{2}$$

where t=1,2,…T, $x_{1,0}$ and $x_{2,0}$ are the constants that take initial values, and e_{1i} and e_{2i} are the white noise error terms. Hatemi-J [22] defined positive and negative shocks as the following: $e_{1i}^{+} = \max(e_{1i}, 0)$, $e_{2i}^{+} = \max(e_{2i}, 0)$, $e_{1i}^{-} = \min(e_{1i}, 0)$, and $e_{2i}^{-} = \min(e_{2i}, 0)$, respectively. Therefore, one can express $e_{1i} = e_{1i}^{+} + e_{1i}^{-}$ and $e_{2i} = e_{2i}^{+} + e_{2i}^{-}$. This implies that

$$x_{1t} = x_{1t-1} + e_{1t} = x_{1,0} + \sum_{i=1}^{t} e_{1i}^{+} + \sum_{i=1}^{t} e_{1i}^{-},$$

and similarly

$$x_{2t} = x_{2t-1} + e_{2t} = x_{2,0} + \sum_{i=1}^{t} e_{2i}^{+} + \sum_{i=1}^{t} e_{2i}^{-}.$$

Finally, in a cumulative form, the positive and negative shocks of each variable can be defined as $x_{1t}^{+} = \sum_{i=1}^{t} e_{1i}^{+}$, $x_{1t}^{-} = \sum_{i=1}^{t} e_{1i}^{-}$, $x_{2t}^{+} = \sum_{i=1}^{t} e_{2i}^{+}$, and$x_{2t}^{-} = \sum_{i=1}^{t} e_{2i}^{-}$. It is important to mention that each positive as well as negative component has a permanent impact on the variables in question. Our objective is to test the Granger-causal relationship between these components. Let us discuss the case of testing for Granger-causal relationship between positive cumulative shocks.[6] Presuming that$x_t^{+} = (x_{1t}^{+}, x_{2t}^{+})$, for the following VAR model of order p, VAR (p), the test for Granger-causality can be implemented:

$$x_t^{+} = \alpha + A_1 x_{t-1}^{+} + \ldots + A_p x_{t-1}^{+} + \xi_t^{+}, \tag{3}$$

where x_t^{+}, α, and ξ_t^{+}, respectively, are the 2×1 vector of the variables, of intercepts, and of error terms (corresponding to each of the variables representing the cumulative sum of positive shocks). The matrix A_r is a 2×2 matrix of parameters for lag order r (r=1,…,p). To select appropriate lag order (p) we used information criterion suggested by Hatemi-J [31] which is defined as follows:[7]

$$HJC = \ln(|\widehat{\Omega}_j|) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right), \quad j = 0, \ldots, p. \tag{4}$$

where $|\widehat{\Omega}_j|$ denotes the determinant of the estimated variance–covariance matrix of the disturbance terms in the VAR model based on lag order j, n is the number of equations in the VAR model and T is the number of observations. Once appropriate lag order is determined we proceeded to test the null hypothesis that kth element of x_t^{+} does not Granger-cause the ωth element of x_t^{+}.[8] Specifically the following hypothesis is tested:

$$H_0: \text{the row } \omega, \text{ column } k \text{ element in } Ar \text{ equals zero for } r = 1, \ldots, p. \tag{5}$$

A Wald test in a compact form can be also expressed. Let us make the following notations:[9]

$$X = (x_1^{+}, \ldots, x_T^{+})(n \times T)\text{matrix},$$
$$D = (\alpha, A_1, \ldots, A_p)(n \times (1+np))\text{matrix},$$

$$Z_t = \begin{bmatrix} 1 \\ x_t^{+} \\ x_{t-1}^{+} \\ \cdot \\ \cdot \\ \cdot \\ x_{t-p+1}^{+} \end{bmatrix} ((1+np) \times 1)\text{matrix, for } t = 1, \ldots, T,$$

$$Z: (Z_0, \ldots, Z_{T-1}) \ ((1+np) \times T)\text{matrix, and}$$
$$\delta = (\xi_1^{+}, \ldots, \xi_T^{+})(n \times T)\text{matrix}.$$

Hence, in compact form we can define the VAR(p) model as the following:

$$X = DZ + \delta \tag{6}$$

In such a case the null hypothesis of non-Granger Granger-causality, H_0: $C\beta$=0, is tested by the following test method:

$$Wald = (C\beta)'[C((Z'Z)^{-1} \Theta S_U)C']^{-1}(C\beta), \tag{7}$$

where β=vec(D) and vec indicates the column-stacking operator; Θ represents the Kronecker product, and C is a $p \times n(1+np)$ indicator matrix with elements ones for restricted parameters and zeros for the

[4] Asymmetric Granger-causality testing can also be implemented for stationary variables. In that case, positive or negative changes can be used instead of the cumulative sums.

[5] The author is grateful to A. Hatemi-J for making available his GAUSS codes of this analysis.

[6] We preferred to use this information criterion because Hatemi-J [39] has shown in the simulation experiments that this information criterion is robust to ARCH and it also performs well when the VAR model is used to forecast.

[7] To conduct tests for Granger-causality between negative cumulative shocks, the vector $x_t^{-} = (x_{1t}^{-}, x_{2t}^{-})$is used.

[8] It should be mentioned that an additional unrestricted lag was included in the VAR model in order to take into account the effect of one unit root as suggested by Toda–Yamamoto [11].

[9] Note that we assume the p initial values for each variable are available. For details on this assumption see Lutkepohl [40].

Table 1
Descriptive statics and correlation analysis.

	Ln(CC)	Ln(EC)	Ln(GDP)	Ln(NG)	Ln(PE)	Ln(TRE)
Mean	11.18127	5.427951	9.008729	7.421268	8.874642	6.189993
Median	11.22790	5.466045	8.993141	7.407136	8.887868	6.203772
Maximum	11.56918	5.953059	9.498666	7.913213	9.154431	6.542939
Minimum	10.67562	4.877949	8.481248	6.845805	8.601188	5.718106
Std. dev.	0.232549	0.275726	0.323829	0.227908	0.131236	0.152111
Skewness	−0.469570	−0.188793	−0.026225	0.003275	−0.056501	−0.456281
Kurtosis	2.169586	1.873388	1.710128	2.352905	1.992096	2.985104
Jarque–Bera	29.07403	26.11876	30.83065	7.747332	19.02983	15.41031
Probability	0.000000	0.000002	0.000000	0.020782	0.000074	0.000450
Correlation						
Ln(CC)	1					
Ln(EC)	0.971787	1				
Ln(GDP)	0.9219582	0.955920	1			
Ln(NG)	**0.2438312**	**0.2428880**	**0.280111**	1		
Ln(PE)	0.8301748	0.8326899	0.8215863	0.6920639	1	
Ln(TRE)	0.6645385	0.6257995	0.6395518	**0.1601528**	**0.5135283**	1

rest of the parameters. S_U is the variance–covariance matrix of the unrestricted VAR model estimated as $S_U = \hat{\delta}_U' \hat{\delta}_U / T - q$, where q is the number of parameters in each equation of the VAR model. If assumption of normality is satisfied, the Wald test statistic above has an asymptotic χ^2 distribution with the number of degrees of freedom equal to the number of restrictions to be tested (in this case equal to p). Further, to avoid the misleading results as our variable are non-normally distributed and also the plausible existence of autoregressive conditional heteroskedasticity (ARCH) effects, we make use of the bootstrapping simulation technique. This approach is implemented as follows.

Firstly the regression Eq. (6) is estimated with restrictions implied by the null hypothesis of Granger non-causality imposed. Thereafter, data is bootstrapped, X_t^*,by using the estimated coefficients from the regression, the original data and the bootstrapped residuals. That is, generate $X^* = \hat{D}Z + \delta^*$. The bootstrapped residuals (δ^*) are created by T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. These bootstrapped residuals are mean-adjusted to make sure that the mean value of the residuals is zero in each bootstrap sample. This is achieved by subtracting the mean value of the resulting set of drawn modified residuals from each of the modified residuals in that particular set. The modified residuals are the regression's original residuals that are adjusted via *leverages* to have constant variance. The bootstrap simulations are repeated ten thousand times and each time the Wald test is estimated. In this way, the distribution of the test is generated. The bootstrap critical value at the α-level of significance (c_a^*) is obtained by taking the (α)th upper quantile of the distribution of the bootstrapped Wald test. The final step in the procedure is to calculate the Wald test using the original data and compare it to the bootstrap critical value. The null hypothesis of non-Granger Granger-causality is rejected at the α level of significance if the Wald test generated in the final step is greater than the bootstrap critical value (c_a^*). The bootstrap critical values are produced for three different significant significance levels i.e., one percentage, five percentage and 10 percentage. The bootstrap simulations are implemented by using statistical software components written in GAUSS by Hatemi-J [22].

3. Empirical findings

Before we move to empirical analysis, we analyzed the descriptive statistics of the variables under consideration to understand their sample property. The normality test results (in Table 1) show that all variables are non-normal, thus, using such variables in the present form with the tests that are based on the normality assumption might be misleading. Skewness statistics show that all variables are negatively skewed (except NG) and Kurtosis statistics show that all variables are leptokurtic.

The correlation analysis between the studied variables show that all the variables are highly correlated (i.e., correlation exceeds 0.6) except for NG, which is not highly correlated with any variable (except PE), and PE which is not highly correlated with TER. Now, if we examine the energy consumption patterns of the USA over a period of time we will find that it has changed significantly over the history of the United States as new energy sources have been developed and as uses of energy changed. Since the beginning, i.e., the period when the USA was formed until the mid- to late-1800s a typical American family used wood (a renewable energy source) as its primary energy source and early industrial growth was powered by water mills. However, in the late 19th century the coal became dominant before being overtaken by petroleum products in the middle of the last century, a time when natural gas usage also rose quickly. Surprisingly, since the mid 20th century, the use of coal has again increased (mainly as a primary energy source for electric power generation), and a new form of energy i.e., nuclear electric power has emerged. After the 1970s, the use of petroleum and natural gas resumed growth, and the overall pattern of energy use since the late 20th century has remained fairly stable. Presently, even after the emergence of new forms of energy sources the three major fossil fuels, namely, petroleum, natural gas, and coal, together provided 87% of total U.S. primary energy over the past decade have dominated the U.S. fuel mix for well over 100 years. However, the recent increases in the domestic production of petroleum liquids and natural gas have prompted shifts between the uses of fossil fuels (largely from coal-fired to natural gas-fired power generation), but the predominance of these three energy sources is likely to continue into the future (for details please refer to *Annual Energy Outlook of* 2014).

Next to examine the trend pattern of the variables we plot the data (see, Fig. 1) which exhibits high fluctuations in all the series indicating that data might be non-stationary in level form. Thus, in the next step we tested the stationarity of data by using ADF and PP test. Our results show that all variables are level-non-stationary but first difference stationary, i.e., they are I(1). Thus we proceed to analyze the cointegration between the variables in the bi-variate framework by using Johansen and Julesis [32] test of cointegration with Pantula principal. The lag-length was determined with AIC. Our results indicated no-cointegration between the tested variables in bivariate framework.[10] However, it should be mentioned that cointegration is

[10] Results of unit root and cointegration are not presented but can be accessed from the author upon request.

not a prerequisite for testing for Granger-causality between integrated variables within the VAR framework as long as additional unrestricted lags are included in the model, according to Toda–Yamamoto [11]. Therefore, for analyzing Granger-causality, we transformed data into first difference form so that variables become stationary and we can have efficient results. Results of symmetric and asymmetric Granger-causality analysis between variants of energy consumption sources and GDP are reported, respectively, in Tables 2 and 4.

It is evident from Table 2 that the null hypothesis that energy consumption does not Granger-cause is rejected at the 1% level of significance for all energy variables considered in the present work. Similarly, for all cases we find the null hypothesis that GDP does not Granger-cause energy consumption is rejected for all energy components. Thus, our findings show the evidence of the bidirectional Granger-causal relationship between energy consumption and economic growth. Further, to analyze the issue in depth we estimated asymmetric Granger-causality test statistics and tested their significance with 10,000 bootstrapped critical values.

We also conduct multivariate diagnostic tests. Based on the results presented in Table 3, one can conclude that the data is not normally distributed and time-varying volatility prevails. Therefore, it is essential to make use of the bootstrap simulation method, as described in the previous section, in order to achieve correct inference. All results from asymmetric Granger-causality analysis are reported in Table 4. It is evident from Table 4 that when the Wald test statistic is used for positive shocks the null-hypothesis for non-Granger-causality is rejected at the 10% level of significance in all cases except two. The case one shows that the CC growth rate does not Granger-cause GDP growth rate while GDP growth rate does, and the case two shows that GDP growth rate does not Granger-cause EC growth rate but the EC growth rate does. Hence, results indicate that there is evidence of a unidirectional Granger-causality from GDP growth rate to CC growth rate and from EC growth rate to GDP growth rate; and there is evidence of bidirectional Granger-causality between NG growth rate and GDP growth rate, PE growth rate and GDP growth rate and TRE growth rate and GDP growth rate. However, when we test the null hypothesis of non-Granger-causality through Wald test statistic for negative shocks we find that the null-hypothesis for non-Granger-causality is rejected at the 10% level of significance in only two cases.

Specifically, we find that the null hypothesis of non-Granger-causality from the growth rate in CC and TRE to growth rate in GDP is rejected at the 5% level of significance. Hence, we have very interesting finding with our asymmetric Granger-causality test that CC growth rate Granger-cause GDP growth rate when shocks are negative, but not when shocks are positive and TRE Granger-cause GDP growth when shows are either positive or negative. Other interesting findings are negative shocks to CC, NG, PE and TRE growth Granger-cause positive shocks of GDP growth rate, whereas positive shocks to GDP growth rate Granger-cause negative shocks of the CC, NG, PE and TRE growth rate. Our results show that there is evidence for the existence of asymmetric Granger-causality i.e., nonlinear Granger-causality (or structurally nonparametric Granger-causality) between CC and GDP, NG and GDP, PE and GDP, and TRE and GDP. In terms of comparison of the findings in the previous studies in USA for variables considered in our study: Payne [15] had found evidence for the absence of Granger-causality between coal consumption and real GDP, unidirectional Granger-causality running from real GDP to natural gas consumption; Yildirim et al. [18] had found a negative relationship between coal consumption and industrial production for the period of 1973:1–1983:4, a positive relationship for 1983:5–1998:4, and a negative cointegration relationship with varying Granger-causal relationship for the period 1983:5–2011:10; Yildirim et al. [19] had found no Granger-causal relationship between real GDP and all of the other renewable energy kinds total renewable energy consumption, geothermal energy consumption, hydroelectric energy consumption, biomass energy consumption and biomass-wood-derived energy consumption; and Kum et al. [26] had found evidence of the bidirectional Granger Granger-causal relationship between natural gas and growth.

Table 2
Results of Granger-causality analysis.

	Test value	TY prob.	BCV at 1%	BCV at 5%	BCV at 10%
Ho: energy consumption does not Granger cause growth					
CC ≠ > GDP	98.677***	0.000	15.337	11.300	9.297
EC ≠ > GDP	86.546***	0.000	15.681	10.889	8.805
NG ≠ > GDP	43.426***	0.000	13.812	10.008	8.142
PE ≠ > GDP	115.510***	0.000	15.264	10.628	8.717
TRE ≠ > GDP	27.661***	0.000	14.920	10.483	8.648
Ho: growth does not Granger cause energy consumption					
GDP ≠ > CC	18.736***	0.001	9.950	6.455	4.988
GDP ≠ > EC	5.337***	0.254	9.852	6.455	4.874
GDP ≠ > NG	24.189***	0.000	9.794	6.187	4.712
GDP ≠ > PE	6.001***	0.199	9.551	6.197	4.738
GDP ≠ > TRE	36.933***	0.000	9.950	6.348	4.847

Notes: (a) The max lag order considered is four. The optimal lag order is selected based on HJC creation mentioned in Eq. (4); (b) the symbol $A \neq > B$ means that A does not cause B; (c) BCV means critical value; (d) *** shows significance at 1% level; (e) TY prob is estimated probability value by the Toda–Yamamoto procedure for the MWALD stat.

4. Conclusions and policy implications

This paper investigated the temporal linkages between variants of energy consumption sources, and GDP of U.S. during January 1973–October 2011. For the analysis, we employed a recent approach of Granger-causality developed by Hatemi-J [22]. Approach of testing Granger-causality between variables

Table 3
Multivariate diagnostic tests for normality and ARCH.

Variables in the VAR model	Multivariate normality: p-values for AR ($p > 1$)			Multivariate ARCH	
	Multivariate Q-test	Adjusted LM test	Multivariate F-test	Asymptotic p-values	Bootstrapped p-values
(CC,GDP)	0.000000	0.000000	0.000000	0.009915	0.010600
(EC,GDP)	0.000000	0.000000	0.000000	0.000021	0.000300
(NG,GDP)	0.000000	0.000000	0.000000	0.029713	0.030500
(PE,GDP)	0.000000	0.000000	0.000000	0.000286	0.001100
(TRE,GDP)	0.000000	0.000000	0.000000	0.000000	0.000100

Notes: 1. The optimal lag-length in the VAR model is based on minimizing the information criterion in Eq. (4). 2. The Doornik and Hansen [33] statistic is applied to test the null hypothesis of multivariate normality. 3. A test provided by Hacker and Hatemi-J [34] was implemented for the multivariate ARCH effects. The simulations of this ARCH test were conducted by a statistical software component produced by Hacker and Hatemi-J [35].

Table 4
Results of asymmetric Granger-causality analysis.

H0: **CC $\neq >$ GDP**	**Test Value**	**BCV at 1%**	**BCV at 5%**	**BCV at 10%**	H0: **GDP $\neq >$ CC**	**Test Value**	**BCV at 1%**	**BCV at 5%**	**BCV at 10%**
$E^+ \neq > Y^+$	7.528	14.174	10.176	8.209	$Y^+ \neq > E^+$	29.330***	18.928	14.198	11.859
$E^- \neq > Y^-$	10.225**	14.255	9.973	8.123	$Y^- \neq > E^-$	6.538	17.310	11.744	9.554
$E^+ \neq > Y^-$	3.352	14.043	9.891	8.062	$Y^+ \neq > E^-$	13.992*	19.437	14.184	11.785
$E^- \neq > Y^+$	20.904***	14.773	10.187	8.306	$Y^- \neq > E^+$	8.563	17.471	11.833	9.732
EC $\neq >$ GDP					GDP $\neq >$ EC				
$E^+ \neq > Y^+$	12.654**	14.124	10.216	8.278	$Y^+ \neq > E^+$	7.415	19.074	13.995	11.731
$E^- \neq > Y^-$	3.388	14.382	9.945	8.120	$Y^- \neq > E^-$	5.343	17.152	12.145	9.820
$E^+ \neq > Y^-$	2.402	13.737	9.878	8.069	$Y^+ \neq > E^-$	7.613	19.224	13.997	11.689
$E^- \neq > Y^+$	3.140	14.466	10.297	8.376	$Y^- \neq > E^+$	4.445	17.868	12.137	9.874
NG $\neq >$ GDP					GDP $\neq >$ NG				
$E^+ \neq > Y^+$	14.538**	17.653	12.648	10.565	$Y^+ \neq > E^+$	11.615**	15.223	10.728	8.791
$E^- \neq > Y^-$	5.386	15.900	10.992	8.722	$Y^- \neq > E^-$	6.933	16.781	11.828	9.595
$E^+ \neq > Y^-$	7.828	15.147	10.904	8.936	$Y^+ \neq > E^-$	12.935**	15.854	11.112	9.102
$E^- \neq > Y^+$	12.501**	15.431	10.901	8.967	$Y^- \neq > E^+$	2.370	17.455	11.571	9.512
PE $\neq >$ GDP					GDP $\neq >$ PE				
$E^+ \neq > Y^+$	10.770*	15.314	10.998	9.047	$E^+ \neq > Y^+$	41.034***	16.701	11.805	9.692
$E^- \neq > Y^-$	5.105	15.011	10.540	8.540	$E^- \neq > Y^-$	5.635	18.264	12.387	9.876
$E^+ \neq > Y^-$	2.138	13.570	9.319	7.452	$E^+ \neq > Y^-$	18.469***	18.721	13.808	11.293
$E^- \neq > Y^+$	17.377***	15.177	10.718	8.748	$E^- \neq > Y^+$	3.532	16.530	10.809	8.620
TRE $\neq >$ GDP					GDP $\neq >$ TRE				
$E^+ \neq > Y^+$	12.086**	15.927	11.383	9.281	$E^+ \neq > Y^+$	24.884***	17.822	12.742	10.674
$E^- \neq > Y^-$	10.610**	14.766	10.225	8.259	$E^- \neq > Y^-$	4.588	19.342	13.183	10.791
$E^+ \neq > Y^-$	0.876	13.690	9.425	7.435	$E^+ \neq > Y^-$	18.575***	19.263	14.155	11.822
$E^- \neq > Y^+$	20.381***	14.672	10.681	8.577	$E^- \neq > Y^+$	6.333	16.723	11.415	9.064

Notes: (a) The max lag order considered is four. The optimal lag order is selected based on minimizing Eq. (4); (b) the symbol $A \neq > B$ means that A does not cause B; (c) BCV means critical value.

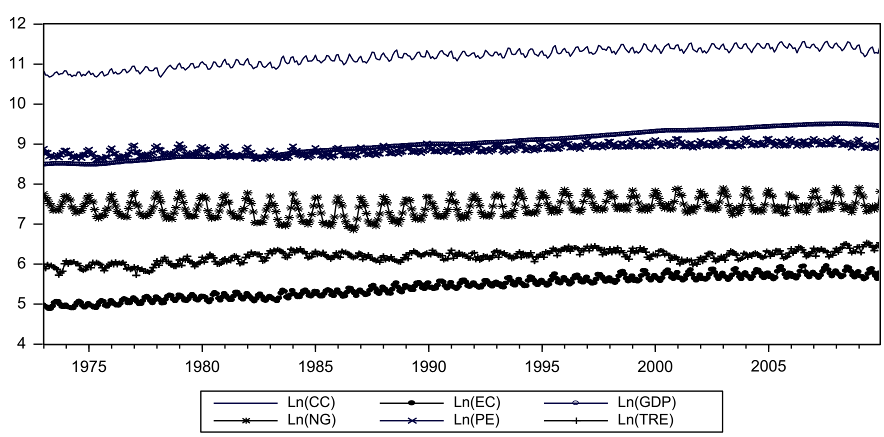

Fig. 1. Graphical plot of variables.

developed by Hatemi-J [22] is asymmetric or nonlinear in the sense that it takes into account impact of positive or negative shocks of one variable on the other. Whereas, most of the literature in the study context uses these approaches based on positive shock only, the present study contributes to the literature by analyzing the impact of both the positive and negative shocks of one variable on the other.

Our results clearly indicated the evidence of existence of asymmetric Granger-causality between CC and GDP, NG and GDP, PE and GDP, and TRE and GDP. This shows that the Granger-causal relationship between these variables is asymmetric and therefore future research, analyzing this issue further, should consider this point. We found the evidence of unidirectional Granger-causality running from GDP growth rate to the CC growth rate and from the EC growth rate to GDP growth rate, Further, evidence of Granger-bidirectional Granger-causality between NG growth rate and GDP growth rate, PE growth rate and GDP growth rate and TRE growth rate and GDP growth rate is also found.

Hence, our result brings out the important policy implication that USA government policies considering the composition of energy use and technological changes may be helpful in moderating environmental degradation and therefore, GHGs. Further, policies such as decreasing energy intensity, increasing energy efficiency in the consumption of RES as well as in NRES, increasing the consumption of total RES (or altering the composition of RES) might be helpful in mitigating the pressure on the environment. In addition to that we recommend to the USA policy makers that

while modeling energy policies they should consider the existence of asymmetric nature of Granger-causality between variants of energy consumption and GDP growth.

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